Driver and road environment assessment for identifying Safety Tolerance Zone using machine learning techniques

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SHORT SUMMARY

Safety Tolerance Zone (STZ) is an abstract entity in nature which refers to a real phenomenon, i.e. self-regulated control over transportation vehicles by human operators in the context of crash avoidance. The aim of this study was to assess driver, road and environment indicators for the identification of STZ. Towards that end, data from a simulator experiment, involving 55 drivers, were analysed. A feature importance algorithm was used to evaluate the significance of variables on forecasting STZ. Additionally, a Neural Network model was implemented for real-time data prediction. Furthermore, a comprehensive assessment of the performance of three machine learning classifiers (i.e. Decision Trees, Random Forests and k-Nearest Neighbors) was made. Neural Networks demonstrated that the level of STZ can be predicted with an accuracy of up to 85.1%. Results also indicated that RF model outperformed the DT and kNN models across all metrics, with accuracy up to 89.1%.

Keywords: Safety Tolerance Zone, speeding, simulator experiment, big data, machine learning techniques.

1. INTRODUCTION

Speeding significantly affects road safety by increasing the physical and mental demands of driving (Wang et al., 2013). It reduces the available reaction time, making it harder to respond to sudden changes or emergencies on the road, thereby heightening the risk of crashes. Furthermore, habitual speeding can lead to poor risk perception, where drivers underestimate the dangers associated with high speeds, leading to overconfidence and risky driving behaviours (Gargoum & El-Basyouny, 2016).

Human operator does not however act in isolation. They are an integral part of the transport system which is made up of a complex interaction of drivers, vehicles, infrastructure, other environmental factors and the rules and regulations that govern them. Multiple factors can contribute to a crash and are related to any part of the transport system and the interaction among the elements in that system (Papadimitriou et al., 2019).

The concept of the Safety Tolerance Zone (STZ) attempts to describe the point at which self-regulated control is considered safe (Michelaraki et al., 2022). Simply described, it is the zone where the demands of the driving task are balanced with the ability of the driver to cope with them. The STZ comprises three phases: normal driving, danger and avoidable accident phase. The normal driving phase represents a low crash risk, where the driver successfully adjusts their behaviour to meet task demands. The danger phase is marked by changes suggesting an increased crash risk, making a crash more likely but not inevitable. The avoidable accident phase occurs when a collision scenario develops, requiring urgent driver intervention to prevent a likely crash. Transitions between these phases are triggered by real-time measurements indicating changes in crash risk.

A schematic overview of the different driving phases of the STZ is depicted in Figure 1.

Figure 1: A schematic overview of the different driving phases of the STZ

Based on the above framework, this study aims to assess driver, road and environment indicators for the identification of Safety Tolerance Zone using machine learning techniques. Towards that end, data from a simulator experiment involving 55 drivers were analyzed.

The paper is organized as follows: First, it outlines the motivation and objectives of the study. Next, the data collection processing is described. The research methodology is then presented, detailing the data collection techniques and the theoretical foundations of the models used. Finally, the study's results are discussed, concluding with the key insights and implications.

2. DATA OVERVIEW

A simulator driving experiment was carried out involving 55 drivers (with total duration of 2 months) and a database consisting of 165 trips was created. Participants were asked to complete a driving behaviour questionnaire to collect detailed information on various aspects of driving, socio-demographics, safety attitude and psychological factors. The simulator trials consisted of three scenarios, as shown in Figure 2.

Figure 2: Overview of the different scenarios of the simulator experiment

A custom car simulator developed by DriveSimSolutions was designed, as shown in Figure 3. The simulator is based on a Peugeot 206 and uses many Original Equipment Manufacturer (OEM) parts, such as the complete dashboard, a working instrument cluster and driving seat to recreate the cockpit of the actual vehicle. The simulator uses fully customizable STISIM Drive 3 software, allowing for creation of custom scenarios and data collection at every simulation update frame. It is also visualized on a triple monitor setup consisting of three 49 inch 4K monitors, providing an 135° field of view.

Figure 3: Car simulator developed by DriveSimSolutions, using OEM Peugeot 206 parts

Figure 4 depicts an overview of an intersection in STISIM Drive 3 for an example of a road environment.

Figure 4: Example of an intersection in STISIM Drive 3

This comprehensive dataset was developed to identify the most significant indicators of driving behaviour. Key variables included time indicators, wiper usage, fuel type, vehicle age and gearbox type. Performance measures encompassed speeding, headway, overtaking, duration, distance, harsh events, as well as demographic factors like gender and age.

3. METHODOLOGY

The structure methodology along with the proposed characteristics to estimate the STZ for speeding is depicted in Figure 5.

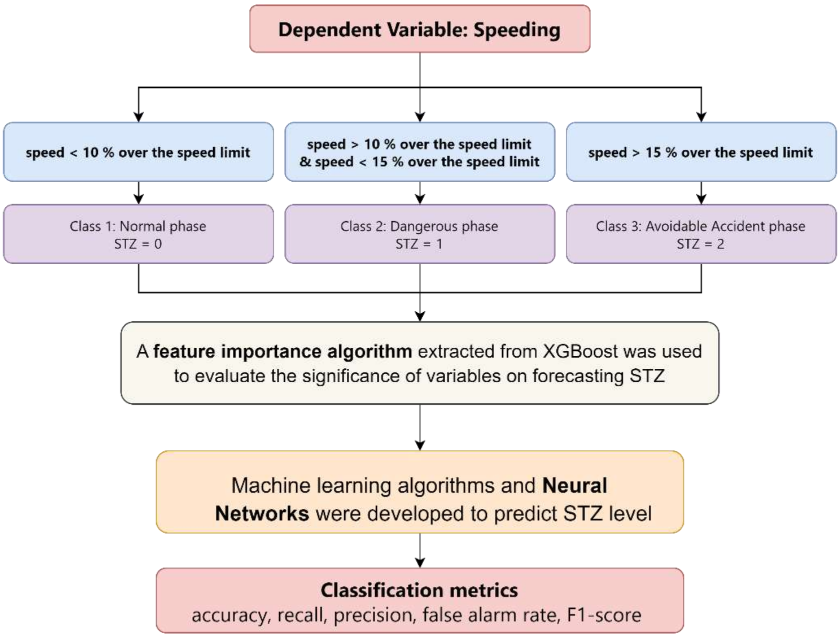

Figure 5: Proposed methodology for the definition of the STZ for speeding

Feature Importance

A feature importance algorithm derived from Extreme Gradient Boosting (XGBoost) was implemented to evaluate the significance of various variables in forecasting STZ. This approach allowed for the selection of the most appropriate independent variables, ensuring that the most influential factors were identified and prioritized in the analysis.

Neural Networks (NNs)

Neural Networks (NNs) are powerful computational models designed to capture complex non-linear patterns in data, emulating the parallel processing of human neurons (Ahad et al., 2016). The multi-layer perceptron architecture used here includes three layers: an input layer, hidden layers and an output layer. The input layer receives driving data such as speed, acceleration and headway. Hidden layers, with variable neuron counts, process these inputs using weighted computations and activation functions to capture intricate relationships between attributes and the target variable; levels of risky driving behaviour. The number of neurons and layers is determined experimentally, balancing learning capacity and generalization. The output layer consolidates information to classify risk levels, with each neuron representing a distinct class.

Decision Trees (DTs)

A Decision Tree (DT) is a supervised learning algorithm used primarily for classification, though it can handle regression tasks. Structured like a tree, it consists of decision nodes, i.e. features with branching rules and leaf nodes i.e. outcomes (Song & Ying, 2015). According to Suthaharan & Suthaharan (2016), the tree begins at the root node, representing the entire dataset and splits into sub-nodes through a series of questions, with each answer determining the next branch. Splitting continues until a stopping criterion is met, such as homogeneous classification within a node or reaching a pre-defined depth. The resulting tree-like structure visually represents decision paths and outcomes, providing a straightforward way to explore solutions based on given conditions.

Random Forests (RFs)

Random Forest (RF) is a robust machine learning technique that combines the outputs of multiple decision trees to deliver a single, accurate result, making it effective for both classification and regression tasks (Breiman & Cutler, 2016). As an ensemble learning method, RF aggregates predictions from individual trees through voting (classification) or averaging (regression). Each tree is built using random subsets of the dataset and features, introducing variability that reduces overfitting and enhances predictive performance. Breiman (1996) introduced the bagging method, a key aspect of RF, which involves sampling data with replacement to create multiple training sets, training models independently and aggregating their predictions to improve accuracy and reduce variance.

K-Nearest Neighbors (kNNs)

The k-Nearest Neighbors (kNN) algorithm is a simple and popular method for classification and regression, based on the principle that similar data points share similar labels or values. It stores the training dataset and predicts outcomes by calculating distances between input data and training points. For classification, it assigns the most common label among the K nearest neighbors, while for regression, it uses the average or weighted average of their values (Nigsch et al., 2006). Performance depends on the choice of K and the distance metric and it can be affected by noisy features or inconsistent scaling.

Model evaluation metrics

In order to compare the classification performance of the several configurations, well-established model evaluation metrics were calculated. The following metrics were utilized, based on the confusion matrix, which provides True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) metrics. The classification algorithms were evaluated using the accuracy, precision, recall, f1-score and false alarm rate as defined below.

Accuracy, which represents the proportion of correctly classified observations, is defined as:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

Precision, which quantifies the number of positive class predictions that actually belong to the positive class, is defined as follows:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall, also known as True Positive Rate, is defined as follows:

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F1-score, which combines precision and recall into a single measure, is defined as follows:

$$f1 - score = \frac{2x\ (Precision)x\ (Recall)}{(Precision)+(Recall)} \quad (4)$$

False alarm rate is defined as follows:

$$False\ Alarm\ Rate = \frac{FP}{FP+TN} \quad (5)$$

4. RESULTS AND DISCUSSION

According to the feature importance analysis, distance travelled, headway, harsh accelerations, harsh brakings and time indicator emerged as the most important factors among all examined indicators. Conversely, car wipers found to be less significant. Lastly, variables related to forward collision warning and pedestrian collision warning had a negligible impact on STZ speeding. Figure 6 provides an overview of the feature importance of independent variables for speeding based on XGBoost algorithm.

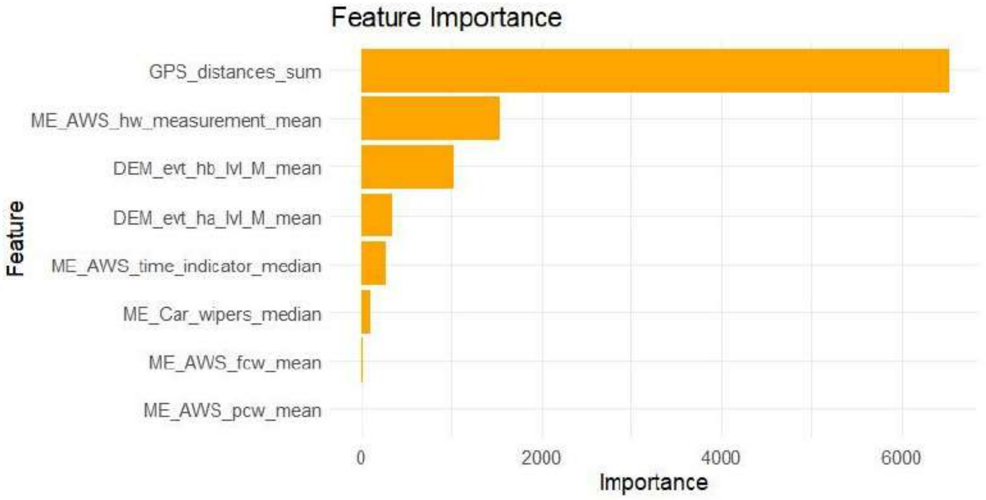

Figure 6: XGBoost feature importance of independent variables for speeding

A dataset of 745,251 rows from the simulator experiment was used and a feed-forward multilayer perceptron NN model was implemented. Based on the feature importance and the significance of the relevant indicators, there were seven neurons in the input layer (i.e. distance travelled, headway, harsh accelerations, harsh brakings, time indicator, wipers and FCW) and three neurons in the output layer (i.e. STZ1, STZ2, STZ3). It should be noted that STZ1 speeding refers to normal phase, STZ2 speeding refers to danger phase, while STZ3 speeding refers to avoidable accident phase.

Figure 7 illustrates the NN model used to predict STZ speeding based on various input features.

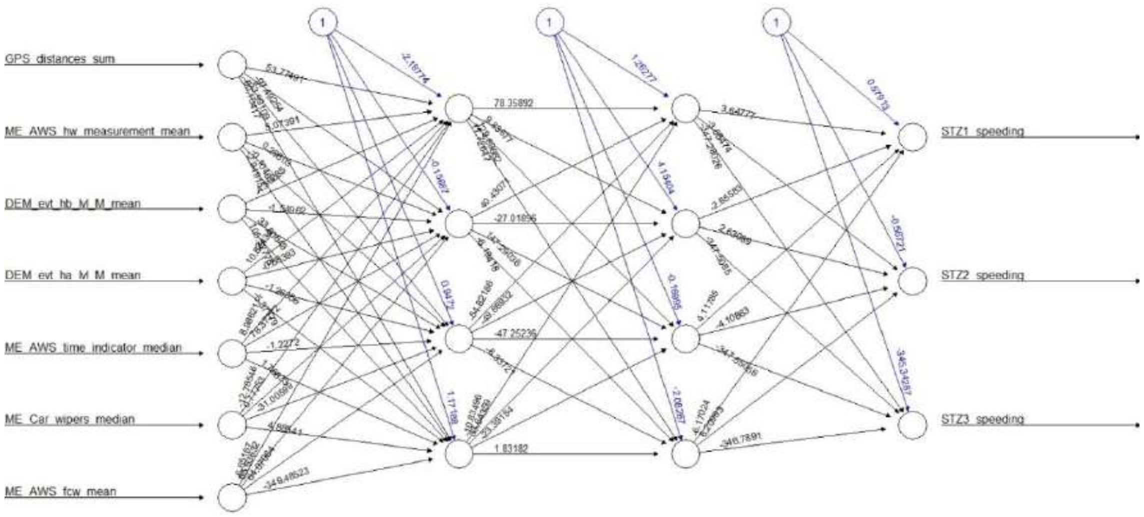

Figure 7: The multi-layer Neural Network model layout for STZ speeding

Then, a confusion matrix which contains three rows and three columns and reports the number of false positives, false negatives, true positives and true negatives was created. More specifically, the confusion matrix illustrates the performance of the classification model for three classes: class 0 (normal level), class 1 (dangerous level) and class 2 (avoidable accident level), as shown in Figure 8.

The model correctly classified 49.12% of the normal phase, 22.09% of the dangerous phase and 14.89% of the avoidable accident phase. Misclassifications include 4.9% of normal misclassified as dangerous and 1.45% as avoidable accidents. For the dangerous phase, 0.35% were misclassified as normal and 0.47% as avoidable accidents. In the avoidable accident phase, 0.7% were misclassified as normal and 6.04% as dangerous.

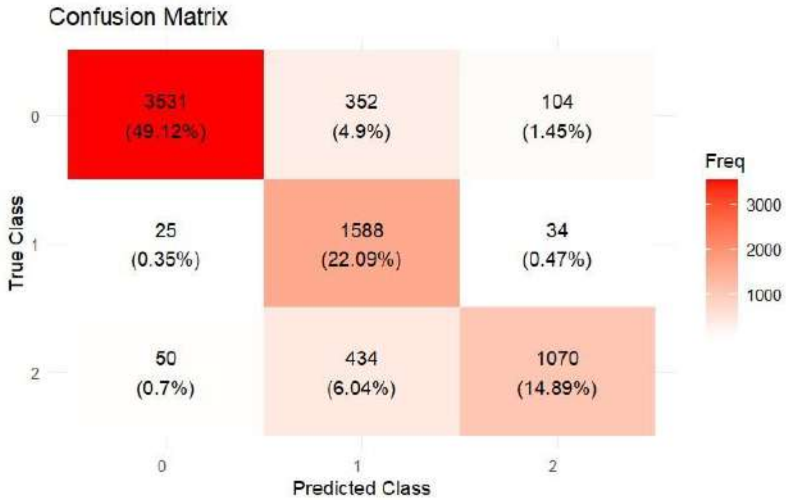

Figure 8: Confusion matrix for the test dataset for Neural Networks – speeding

Table 1 presents the assessment of the classification model for speeding. The model performs best in predicting the normal phase, achieving 92.1% accuracy, 97.9% precision, 88.6% recall and a false alarm rate of 2.8%. For the dangerous phase, it shows 87.4% accuracy, 66.9% precision, 96.4% recall and a false alarm rate of 15.5%. In the avoidable accident phase, the model achieves 90.7% accuracy, 81.0% precision, 54.7% recall and a false alarm rate of 2.4%. Overall, the model has 85.1% accuracy, 83.9% precision, 80.4% recall and a false alarm rate of 6.9%.

Table 1: Evaluation metrics for NN for speeding

Model Fit measures	0	1	2	Total
Accuracy	0.921	0.874	0.907	0.851
Precision	0.979	0.669	0.810	0.839
Recall	0.886	0.964	0.547	0.804
F1 Score	0.930	0.790	0.653	0.816
False alarm rate	0.128	0.255	0.224	0.169

**0 refers to normal phase, 1 refers to dangerous phase, 2 refers to avoidable accident phase*

Table 2 summarizes the performance of three machine learning classifiers across four metrics: accuracy, precision, recall and F1-score. Overall, RF demonstrates the best performance with an accuracy of 89.1%, precision of 90.8% and recall of 87.5%. DT shows moderate performance with an accuracy of 85.2%, precision of 85.3% and recall of 83.1%. kNN performs the lowest among the three, with an accuracy of 81.5%, precision of 78.3% and recall of 79.6%. These results highlight RF as the most effective classifier, followed by DT and then kNN.

Table 2: Evaluation metrics for classification models for speeding

Model Fit measures	0	1	2	Total
		Accuracy		
DT	0.887	0.853	0.816	**0.852**
RF	0.930	0.878	0.865	**0.891**
kNN	0.825	0.803	0.818	**0.815**
		Precision		
DT	0.873	0.866	0.821	**0.853**
RF	0.952	0.815	0.888	**0.908**
kNN	0.833	0.789	0.771	**0.783**
		Recall		
DT	0.860	0.834	0.801	**0.831**
RF	0.891	0.872	0.863	**0.875**
kNN	0.843	0.788	0.759	**0.796**
		F1 Score		
DT	0.815	0.792	0.733	**0.804**
RF	0.878	0.741	0.713	**0.849**
kNN	0.803	0.687	0.652	**0.791**

**0 refers to normal phase, 1 refers to dangerous phase, 2 refers to avoidable accident phase*

Figure 9 depicts the bar chart, comparing the performance of three classifiers for speeding. It can be observed that RF consistently outperforms the other two classifiers in all metrics, showing the highest scores. DT and kNN show relatively close performance, with kNN generally having the lowest scores among the three.

Figure 9: Comparison of classifier metrics of machine learning techniques for speeding

5. CONCLUSIONS

The current study aimed to assess driver, road and environment indicators for the identification of STZ using machine learning techniques. For this purpose, data were collected and analyzed from a simulator experiment with 55 drivers.

To achieve these objectives, a feature importance analysis (e.g. XGBoost) was performed to evaluate the relevance of various variables in predicting STZ levels. Subsequently, machine learning models, such as NNs, were employed to make accurate data-driven predictions. Additionally, a detailed evaluation of three machine learning classifiers (DT, RF and kNN) was conducted to predict STZ levels for speeding.

The analysis identified distance travelled, headway, harsh accelerations, harsh brakings and time indicator as the most influential factors. NNs achieved exceptional predictive accuracy, with an accuracy rate of up to 85.1%, demonstrating the model's robustness in identifying positive cases and its effectiveness in detecting safety-critical scenarios, as evidenced by its high recall. This indicates a well-rounded and reliable predictive capability for speeding in the simulator context.

The results revealed that RF models outperformed DT and kNN models across all metrics, achieving an accuracy of up to 89.1%. While DT models showed satisfactory performance, kNN models consistently delivered the lowest but moderate scores, making them the least effective among the classifiers for this task. These performance differences highlighted the importance of selecting the appropriate model based on data characteristics and the precision-recall trade-offs required for practical applications.

Despite the robust methodologies employed, certain limitations of the study should be acknowledged. Firstly, the limited sample size for the simulator experiment may affect the generalizability of the findings. While the data provided valuable insights, a larger sample would improve the reliability and applicability of the results. Secondly, although the models demonstrated strong performance, the integration of advanced deep learning approaches, such as Recurrent or Convolutional Neural Networks, might enhance predictive capabilities. The comparatively lower performance of the kNN model suggests that further optimization and tuning are needed to improve its outcomes.

Future research could explore additional methods of analysis, such as imbalanced learning, factor analysis and models that account for unobserved heterogeneity. Econometric techniques could also be applied. Advanced deep learning models, like Long Short-Term Memory (LSTM) networks, which have shown superior performance in related studies, warrant exploration. Lastly, integrating contextual information, such as road infrastructure and traffic patterns, could enhance model accuracy and applicability.

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